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Introduction

Non-invasive Brain-Computer Interfaces (BCIs) are largely used to produce thought-provoked action, by exploiting the ability of subjects to voluntary modulate their brain activity through mental imagery. Despite its clinical applications [Jin, 2012; Prasad, 2010], controlling a BCI appears to be a learned skill. Several weeks or even months are needed to reach relatively high-performance in BCI control, without being sufficient for 15 to 30 % of the users [Allison, 2010; Vidaurre, 2010]. This gap has motivated a deeper understanding of mechanisms associated with motor imagery (MI) tasks [Kaiser, 2014; Perdikis, 2014]. If similarities have been shown between MI-based BCI learning and motor sequence learning [McDougle, 2016; Wander, 2013], our understanding of the involved processes is still incomplete. Among the advanced reasons are the lacks of longitudinal studies long enough to observe consolidation effects associated with learning process, and of proper learning metrics based on the neurophysiology [Perdikis, 2018]. Here, we expected that MI-BCI learning is associated with the recruitment of areas distributed across the cortex beyond those targeted by the BCI. We also hypothesized that the associated properties, in terms of activations and functional connectivity, predict the learning success.

Methods

We recorded brain signals electroencephalography (EEG) while subjects performed a BCI task twice in a week during two weeks. It consisted of modulating their brain activity in the α-β band to control the vertical position of a moving cursor displayed on a screen. To go up, the subjects imagined a grasping movement with the right hand and to go down, they remained at rest.

Twenty BCI-naive subjects (aged 27.45±4.01 years, 12 men), all right-handed, participated in the study. After having removed the electrophysiological artifacts by using the Independent Component analysis method [Bell, 1995], we performed the source reconstruction on the epoched data via the Boundary Element Method followed by the weighted Minimum Norm Estimate. We performed a paired t-test on power spectra obtained from the MI and the Rest conditions. Statistics were corrected for multiple comparisons using the cluster approach by using the sum of the t-values within every cluster.

The functional connectivity analysis was performed through the computation of the imaginary coherence between each pair of region of interest based on [Sekihara, 2011]. Finally, node strength was obtained by summing the values of the associated row in the connectivity matrix.

Results

In both α and β ranges, we found a progressive involvement of distributed sources in the cortical hemisphere contralateral to the movement corresponding to a significant power decrease ($p<0.025$), more pronounced in the primary somatosensory cortex, the primary motor cortex, the frontal, the prefrontal, the temporal and the parietal areas. The observed decreases tended to focus more on the contralateral pre-and postcentral gyri at the end of the training. We found a progressive decrease of task-related connectivity in both α and β ranges across sessions. Significant across-session decreases were spatially diffused involving bilaterally frontal, temporal and occipital areas in α ranges, while they were more focused over the left primary motor cortex, the left central and parietal areas in the β ranges ($p < 0.025$).

Power changes in α and β ranges significantly predicted the BCI accuracy in the subsequent session ($p < 0.005$ in α_2). The connectivity decrease in the frontal and the temporal areas was associated with a better future performance in α_2 (Figure).

Conclusion

We found cortical changes associated with a dynamic brain reorganization during BCI training. They were characterized by a local increase of sensorimotor activation which was paralleled by a global decrease of functional connectivity. Notably, these changes could predict the future BCI performance.

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Figure

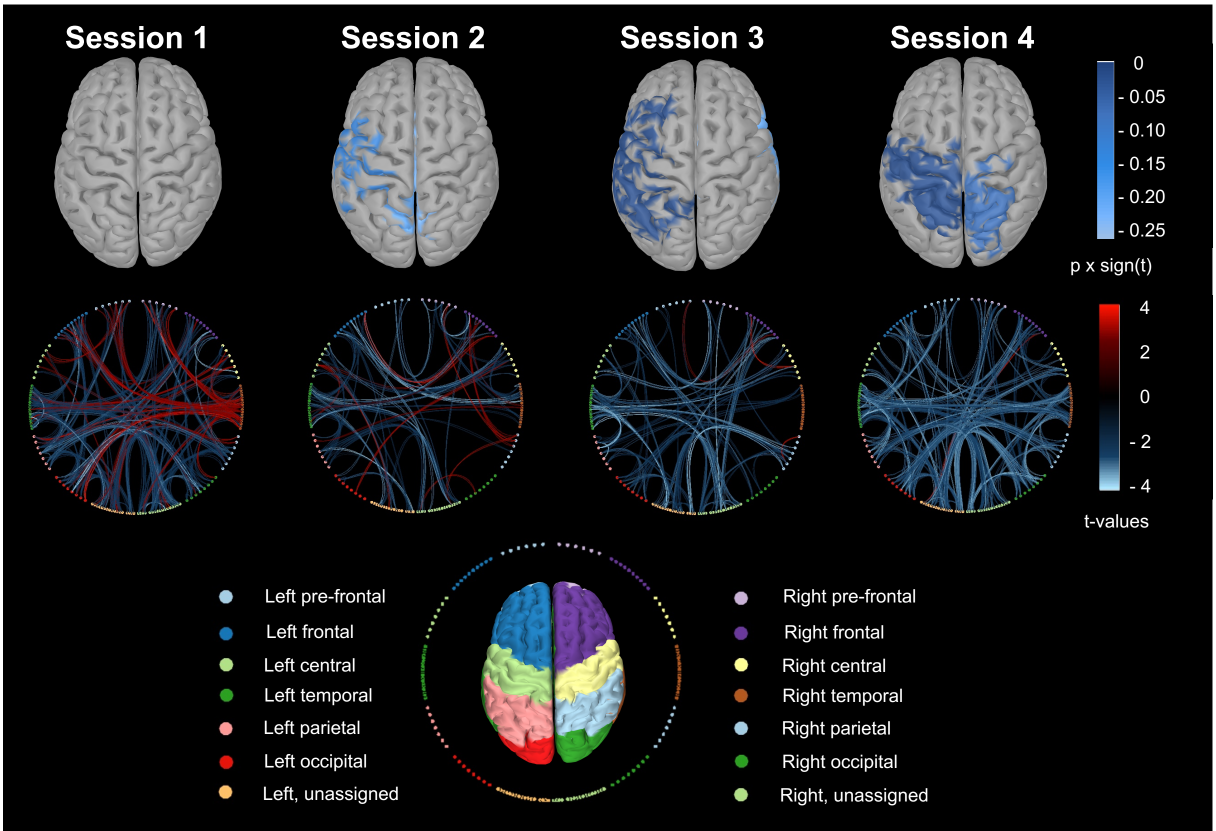

Figure. Contrast between motor imagery and rest conditions within the α_2 band. On the first row, we displayed the contrast maps between the conditions, in terms of activations. Cluster-based permutation results computed from the group analysis performed across the 20 subjects within the MNI template. Here, we plotted the obtained p-values multiplied by the sign of the t-values resulting from the paired t-test. On the second row, we displayed the cortical connectivity changes in BCI training. Results are represented on a circular graph where nodes correspond to different regions of interest (ROIs) and links code the statistical values resulting from the paired t-test performed between the conditions ($p<0.005$).The color of each node, corresponds to a specific macro-area as provided by the Brainstorm software; "unassigned" labels mean that the ROI cannot be properly attributed to a specific macro-area.